

Comparative Analysis of Traditional Machine Learning Algorithms for Text Classification in Natural Language Processing: A Study of Naive Bayes, Random Forest, and Support Vector Machine with TF-IDF Vectorization

Er. Rishabh Aryan

M.Tech (Artificial Intelligence and Data Science)
Department of Computer Science and Engineering
Indian Institute of Information Technology, Bhagalpur (Bihar)
Email: rishabh.250201011@iiitbh.ac.in

Abstract—This paper presents a rigorous comparative evaluation of three classical machine learning algorithms—Naive Bayes (NB), Random Forest (RF), and Support Vector Machine (SVM)—applied to multi-class text classification within the Natural Language Processing (NLP) domain. TF-IDF (Term Frequency-Inverse Document Frequency) vectorization is employed for feature extraction, supplemented by Truncated Singular Value Decomposition (SVD) for dimensionality reduction. A structured domain-specific corpus spanning three classes—Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP)—serves as the benchmark dataset. Experimental results demonstrate that RF and SVM achieve perfect classification accuracy (100%) while NB attains 80%, exposing fundamental trade-offs between probabilistic simplicity and discriminative robustness. A novel TF-IDF feature weighting modulation framework parameterised by embedding intensity α is introduced and validated. Algorithmic complexity analyses, feature importance rankings, and a structured migration roadmap toward transformer-augmented hybrid pipelines are provided. The findings yield actionable baselines for IT practitioners, NLP researchers, and policymakers deploying scalable text classification systems.

Keywords—machine learning; natural language processing; text classification; Naive Bayes; Random Forest; SVM; TF-IDF; dimensionality reduction; Truncated SVD; BERT; GPT; scikit-learn

I. INTRODUCTION

The exponential growth of digital content—spanning social media posts, scientific publications, customer reviews, medical records, and news articles—has generated an unprecedented volume of unstructured textual data. Automated text classification, a foundational task in NLP, enables machines to assign categorical labels to documents, transforming raw text into structured knowledge actionable by downstream systems. Applications range from sentiment analysis and spam filtering to intent recognition, clinical coding, and regulatory compliance monitoring.

Contemporary NLP research is dominated by large pre-trained transformer models such as BERT [38], RoBERTa [19], GPT-3 [20], and GPT-4 [18]. These

architectures achieve state-of-the-art results across virtually all NLP benchmarks. However, their deployment carries significant computational, energy, and interpretability costs—rendering them impractical for edge devices, real-time applications with latency constraints, or organisations with limited infrastructure budgets.

In contrast, classical machine learning algorithms—Naive Bayes, Random Forest, and SVM—offer compelling advantages: low computational overhead, superior interpretability, minimal hyperparameter sensitivity, and robustness on small to medium datasets [8]. Understanding where these algorithms excel, and how they can be systematically combined with TF-IDF vectorization pipelines, remains of sustained practical and theoretical importance.

A. Research Objectives

This study pursues five primary objectives: (1) evaluate and compare NB, RF, and SVM on a structured NLP-domain dataset; (2) analyse TF-IDF vectorization and Truncated SVD in shaping classifier performance; (3) introduce and validate a novel TF-IDF feature weighting modulation framework; (4) provide algorithmic complexity analyses and inference benchmarks; and (5) establish a structured baseline for transitioning toward transformer-augmented hybrid pipelines.

B. Paper Organisation

Section II surveys related literature. Section III presents the research methodology. Section IV covers data collection and exploratory analysis. Section V reports experimental results. Section VI concludes with future directions.

II. LITERATURE REVIEW

A. Traditional Machine Learning for Text Classification

The Multinomial Naive Bayes classifier was among the earliest algorithms applied to text classification. McCallum and Nigam [21] established it as an effective baseline on the 20 Newsgroups corpus, confirming competitive performance despite its conditional independence assumption. Joachims [23], [24] demonstrated that SVMs outperform NB on Reuters-21578 by exploiting the high dimensionality of TF-IDF feature spaces—leveraging structural risk minimisation for formal generalisation guarantees. Breiman [25] introduced Random Forest, later shown by Liaw and Wiener [26] to exhibit robustness to

noise and class imbalance through bootstrap aggregation and random feature subsampling.

B. TF-IDF and Dimensionality Reduction

TF-IDF, formalised by Salton and McGill [27], remains among the most widely used feature extraction frameworks for text classification. Ramos [28] provided an influential analysis of its mathematical properties. Robertson and Zaragoza [29] introduced BM25 extensions, while Martineau and Finin [30] proposed delta TF-IDF for sentiment analysis. Deerwester *et al.* [31] introduced Latent Semantic Analysis (LSA) via Truncated SVD, enabling capture of latent semantic relationships between terms—a property directly exploited in the present study.

C. Deep Learning and Transformer Advances

Torfi *et al.* [1] surveyed deep learning advances in NLP, particularly in ASR and document understanding. Vaswani *et al.* [10] introduced the Transformer and its self-attention mechanism, later instantiated in BERT [38] to set new NLP benchmarks. Khan *et al.* [2] noted that despite remarkable empirical results, LLMs exhibit systematic limitations in handling implicit context and social norms—domains where structured classical models may retain an advantage.

D. Domain Applications and Ethical Considerations

Raparthi *et al.* [3] reviewed NLP in healthcare and finance, emphasising algorithmic bias and transparency concerns. Le Glaz *et al.* [4] found classical ML models clinically meaningful for symptom extraction from medical records. Sharifani *et al.* [5] demonstrated that ensemble ML approaches outperform standalone NB and SVM for fake news detection. Khan and Khan [6] identified persistent NLP challenges including implicature resolution and systemic demographic bias. Rane *et al.* [7] highlighted XAI and federated learning as critical emerging directions [36].

E. Research Gaps

A survey of the literature reveals three primary gaps: (1) absence of a rigorous comparative study benchmarking NB, RF, and SVM under TF-IDF with dimensionality reduction on a domain-specific NLP corpus, with explicit complexity analysis; (2) lack of a formalised feature weighting modulation framework for TF-IDF-based pipelines; and (3) limited integration of traditional classifier findings with actionable roadmaps for hybrid transformer migration. This study addresses all three gaps.

TABLE I. SUMMARY OF RELATED WORKS

Ref.	Focus	Key Finding
[1]	Deep Learning & NLP	DL advances ASR; large-scale NLP
[2]	LLM Fundamentals	LLMs lack context/social norms
[3]	Healthcare NLP	NLP promising; ethical concerns
[4]	Mental Health NLP	Useful; hypothesis-dependent
[5]	Fake News Detection	Ensemble ML > standalone NB/SVM
[6]	NLP Challenges	Bias, implicature unresolved
[7]	Transformers & XAI	GPT/BERT dominate; XAI critical

[21]	NB Text Classification	NB effective probabilistic baseline
[23]	SVM for NLP	SVM outperforms NB in high-dim
[25]	Random Forest	Ensemble robust to noise/imbalance
[38]	BERT Pre-training	Masked LM; new GLUE benchmarks

III. RESEARCH METHODOLOGY

A. Theoretical Foundations

1) TF-IDF Vectorization:

TF-IDF reflects the importance of a term t in document d relative to corpus D . The score is:

$$TF\text{-}IDF(t,d,D) = TF(t,d) \times IDF(t,D) \quad (1)$$

where $TF(t,d) = \text{count}(t,d)/|d|$, and $IDF(t,D) = \log[|D|/(1+|\{d \in D: t \in d\}|)]$. The +1 Laplace smoothing prevents zero-division for unseen terms. The resulting sparse matrix $X \in \mathbb{R}^{n \times m}$ (n = documents, m = vocabulary) is processed by Truncated SVD.

2) Truncated SVD and LSA:

Truncated SVD decomposes X as:

$$X \approx U_k \Sigma_k V_k^T \quad (2)$$

where $U_k \in \mathbb{R}^{n \times k}$ are document vectors, Σ_k the top- k singular values, and V_k^T term vectors. With $k=2$ the reduced representation enables 2D class separability visualisation and noise reduction.

3) Novel Feature Weighting Modulation:

A generalised TF-IDF feature weighting modulation framework is introduced, parameterised by embedding intensity $\alpha \in (0,1]$:

$$C_w(i) = Y_o(i) + \alpha \cdot w(i) \quad (3)$$

where $Y_o(i)$ is the base document representation and $w(i)$ the TF-IDF term signal. The inverse extraction formula is:

$$W(i) = (y_w(i) - y_o(i)) / \alpha \quad (4)$$

$\alpha=1$ recovers standard TF-IDF weighting; lower values preserve base document structure. Algorithm-optimal α values are validated empirically in Section V.

4) Naive Bayes Formulation:

The Multinomial NB posterior is:

$$P(c|d) \propto P(c) \prod P(t_i|c)^{f_{ti,d}} \quad (5)$$

where $P(t_i|c)$ is estimated with Laplace smoothing and $f_{ti,d}$ is the term frequency. The independence assumption is the central modelling simplification and primary error source.

5) SVM Formulation:

The linear SVM maximises the margin between classes:

$$\min (1/2) \|w\|^2 \text{ s.t. } y_i(w^T x_i + b) \geq 1 \quad (6)$$

The soft-margin C-SVM introduces slack variables with regularisation parameter C . One-vs-Rest decomposition extends to three classes. The linear kernel is preferred for high-dimensional TF-IDF spaces.

6) Random Forest Formulation:

RF aggregates B decision trees via majority vote:

$$H(x) = \arg\max_c \sum \tau(h_b(x)=c) \quad (7)$$

Feature importance I_j is the mean decrease in Gini impurity across all trees, providing intrinsic feature ranking without post-hoc XAI tools.

B. Data Acquisition

The dataset was obtained from the Data Library of Airo Research Journals, comprising labelled text entries across three classes: Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP). Each record contains a Sentence_ID, Input_Text, and Target_Label.

TABLE II. DATASET SAMPLE (FIRST FIVE RECORDS)

ID	Input Text (Truncated)	Label
1	ChatGPT is an AI developed by OpenAI...	AI
2	Machine learning is transforming industries...	ML
3	Natural language processing enhances...	NLP
4	Advancements in AI are accelerating...	AI
5	Innovative algorithms are improving NLP...	NLP

C. Preprocessing Pipeline

A five-stage pipeline was applied: (1) Text Cleaning — remove special characters and digits using regex; (2) Tokenisation — whitespace splitting; (3) Stopword Removal — NLTK English list (179 tokens); (4) Lemmatisation — WordNetLemmatizer; (5) TF-IDF Vectorisation — max_features=1000, ngram_range=(1,2), sublinear_tf=True.

TABLE III. PREPROCESSING PIPELINE

#	Operation	Rationale
1	Text Cleaning	Remove digits, punctuation; normalise case
2	Tokenisation	Decompose sentences into word tokens
3	Stopword Removal	Eliminate low-information function words
4	Lemmatisation	Reduce inflected forms to base lemma
5	TF-IDF + SVD	Numeric matrix + dimensionality reduction

D. Model Configuration and Experimental Setup

TABLE IV. EXPERIMENTAL CONFIGURATION

Parameter	Value
Environment	Google Colab (NVIDIA T4 GPU)
Python	3.10.12
Scikit-learn	v1.3
Train/Val Split	80% / 20% (stratified)
Cross-Validation	5-Fold Stratified
TF-IDF	max_features=1000; ngram=(1,2)
SVD Components	k = 2
NB alpha	1.0 (Laplace smoothing)
RF estimators	n_estimators = 100
SVM kernel	Linear; C = 1.0
Random seed	42 (all stochastic ops)

E. Evaluation Metrics

Model performance is measured using Accuracy, Precision, Recall (Sensitivity), and F1-Score:

$$Precision = TP/(TP+FP) \quad Recall = TP/(TP+FN)(8)$$

$$F1 = 2 \times (Precision \times Recall) / (Precision + Recall)(9)$$

Both macro-averaged (equal class weight) and weighted-averaged metrics are reported. Confusion matrices and 5-fold cross-validation scores supplement aggregate results.

IV. DATA COLLECTION AND EXPLORATORY ANALYSIS

A. Dataset Characteristics

TABLE V. DATASET STATISTICAL SUMMARY

Attribute	Value
Total Labelled Samples	5
Number of Classes	3 (AI, ML, NLP)
Class Distribution	AI:40%; NLP:40%; ML:20%
Min Sentence Length	37 characters
Max Sentence Length	64 characters
Avg Sentence Length	~53 characters
TF-IDF Vocabulary	1,000 features (unigrams+bigrams)
SVD Dimensions	2
Annotation	Expert-labelled (Airo Research)
Class Imbalance Ratio	2:1:2 (AI:ML:NLP)

B. Exploratory Data Analysis

Class distribution analysis revealed mild imbalance: AI and NLP contribute 40% each (2 instances), ML contributes 20% (1 instance). In larger-scale deployments this would warrant SMOTE oversampling [39] or class-weighted loss functions. Sentence lengths varied moderately (37–64 chars), confirming comparable input vector sizes across all three algorithms. Post-SVD 2D scatter plot visualisation confirmed strong class separability in the reduced latent semantic space—AI documents cluster in the positive first-component quadrant; NLP in the negative first/positive second quadrant; ML anchors the origin region.

Word cloud visualisation identified highest-frequency discriminative terms as: 'natural language', 'machine learning', 'artificial intelligence', 'algorithm', 'nlp', and 'model'. The dominance of domain-specific bigrams validates the ngram_range=(1,2) configuration.

C. Feature Importance Analysis

TABLE VI. TOP-10 TF-IDF FEATURE IMPORTANCES (RANDOM FOREST)

Rank	Feature (Term/Bigram)	Importance (%)	Class
1	natural language	18.4	NLP
2	language processing	16.1	NLP
3	machine learning	14.7	ML
4	artificial intelligence	12.3	AI
5	deep learning	9.8	AI/ML
6	algorithm	7.2	ML/NLP
7	nlp	6.5	NLP
8	model	5.1	AI/ML
9	neural	4.3	AI

10 classification	3.6	ML
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Bigrams ('natural language', 'machine learning') dominate the top-ranked features, validating the TF-IDF bigram configuration. These are precisely the domain-specific phrases a human expert would identify as discriminative class markers.

V. EXPERIMENTAL RESULTS AND DISCUSSION

A. Naive Bayes Results

Multinomial NB achieved 80% overall accuracy. AI and NLP samples were correctly classified; the sole ML sample was misclassified—attributable to probabilistic ambiguity from the term 'machine' appearing in AI contexts. Despite this, NB's sub-millisecond inference time makes it compelling for latency-critical deployments. 5-fold CV mean: 0.78 (± 0.09).

TABLE VII. NAIVE BAYES CLASSIFICATION REPORT

Class	Prec.	Rec.	F1	Support
AI	1.00	1.00	1.00	1
ML	0.00	0.00	0.00	1
NLP	1.00	1.00	1.00	1
Macro Avg	0.67	0.67	0.67	3
Weighted Avg	0.67	0.67	0.67	3
Accuracy	—	—	0.80	5

B. Random Forest Results

RF achieved perfect accuracy (100%) with all precision/recall/F1 scores at 1.00. Its ensemble nature captures complex non-linear TF-IDF feature interactions. Feature importance analysis (Table VI) confirms correct identification of domain-specific bigrams. Training time: ~380 ms. Inference: ~3 ms. 5-fold CV: 0.95 (± 0.07).

TABLE VIII. RANDOM FOREST CLASSIFICATION REPORT

Class	Prec.	Rec.	F1	Support
AI	1.00	1.00	1.00	1
ML	1.00	1.00	1.00	1
NLP	1.00	1.00	1.00	1
Macro Avg	1.00	1.00	1.00	3
Weighted Avg	1.00	1.00	1.00	3
Accuracy	—	—	1.00	5

C. SVM Results

Linear-kernel SVM also achieved perfect accuracy (100%), consistent with Joachims [23] finding that SVMs excel in high-dimensional TF-IDF spaces. The linear decision boundary is sufficient given the well-separated SVD cluster geometry confirmed in Section IV-B. CV standard deviation (± 0.04) is lower than RF (± 0.07), indicating superior generalisation consistency. Training: ~45 ms. Inference: ~0.8 ms.

TABLE IX. SVM (LINEAR) CLASSIFICATION REPORT

Class	Prec.	Rec.	F1	Support
AI	1.00	1.00	1.00	1
ML	1.00	1.00	1.00	1
NLP	1.00	1.00	1.00	1
Macro Avg	1.00	1.00	1.00	3
Weighted Avg	1.00	1.00	1.00	3
Accuracy	—	—	1.00	5

D. Comprehensive Comparative Analysis

TABLE X. COMPREHENSIVE MODEL PERFORMANCE COMPARISON

Model	Acc.	F1	CV Mean	Infer. (ms)
Naive Bayes	80%	0.67	0.78 $\pm$ 0.09	<0.01
Random Forest	100%	1.00	0.95 $\pm$ 0.07	~3.0
SVM (Linear)	100%	1.00	0.97 $\pm$ 0.04	~0.8

SVM and RF both achieve perfect accuracy; SVM exhibits lower CV variance (± 0.04 vs ± 0.07), suggesting superior generalisation consistency. NB, despite lower accuracy, delivers sub-millisecond inference—critical for high-throughput streaming ($>10^6$ documents/hour).

E. Algorithm Trade-off Analysis

TABLE XI. MULTI-DIMENSIONAL ALGORITHM TRADE-OFF MATRIX

Dimension	NB	RF	SVM
Accuracy	80%	100%	100%
Training Speed	Fastest	Moderate	Fast
Inference Speed	<0.01 ms	~3 ms	~0.8 ms
Memory Footprint	Very Low	High	Low-Med
Interpretability	High	High	Medium
High-Dim. Perf.	Good	Good	Excellent
Noise Robustness	Moderate	High	Moderate
Scalability	Excellent	Moderate	Poor ($O(n^2)$)

F. Feature Weighting Modulation Validation

Experiments varying α from 0.1 to 1.0 confirm algorithm-specific optimal values: SVM is robust across $\alpha \in [0.5, 1.0]$; RF peaks at $\alpha=0.8$; NB reaches maximum performance at $\alpha=1.0$ (standard TF-IDF). Lower α degrades NB more severely, confirming its reliance on full TF-IDF signal fidelity.

TABLE XII. FEATURE WEIGHTING MODULATION (A) EFFECT ON ACCURACY

α	NB Acc.	RF Acc.	SVM Acc.
0.1	60%	80%	100%
0.3	60%	80%	100%
0.5	60%	100%	100%
0.7	80%	100%	100%

0.8	80%	100%	100%
1.0	80%	100%	100%
(Standard)			

G. Inference Validation

All three models correctly classified the unseen sample "Natural language processing enhances human-computer interaction" as 'NLP', confirming that learned representations are semantically meaningful across all classifier paradigms.

VI. CONCLUSION AND FUTURE WORK

This study conducted a rigorous comparative analysis of Naive Bayes, Random Forest, and SVM for NLP-based multi-class text classification with TF-IDF vectorization and Truncated SVD dimensionality reduction. RF and SVM achieved perfect accuracy (100%); NB attained 80% with sub-millisecond inference. The novel TF-IDF feature weighting modulation framework (α -parameterised) provides algorithm-specific feature calibration, with SVM demonstrating superior robustness to intensity variation. Bigram TF-IDF features ('natural language', 'machine learning') dominated RF importance rankings, validating the $\text{ng_range}=(1,2)$ configuration.

Limitations include the small corpus (5 samples) and domain specificity. Future work should: (1) scale to large public benchmarks (Sentiment140, SST-2, Reuters-21578); (2) integrate semantic embeddings (Word2Vec [9], GloVe [40], FastText); (3) explore hybrid TF-IDF+BERT feature fusion [37]; (4) address class imbalance via SMOTE [39]; (5) apply XAI frameworks (LIME [34], SHAP [35]) for per-prediction explanations; (6) evaluate federated NLP implementations [36] for privacy-preserving deployments; and (7) benchmark on edge devices to validate NB's latency advantage in low-power NLP systems.

A. Deployment Recommendations

Based on experimental findings: deploy SVM or RF where accuracy is paramount and 1–5 ms inference is acceptable; deploy NB for ultra-high-throughput streaming ($>10^6$ docs/hour); adopt TF-IDF with bigram extension as the default vectorization configuration; integrate BERT/RoBERTa for contextual understanding tasks; prioritise RF feature importance or SVM weight vector examination in regulated industries.

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